
Multiple Sclerosis Progression Detection in Brain MRI Images using Hybrid Segmentation

(IJCST) International Journal of
Communication Systems and Network
Technologies

ISSN Number: 2053-6283

Volume 5, Issue No. 2, 92–106

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<https://journals.mirlabs.in/index.php/ijcsnt>

DOI-10.18486/ijcsnt/5.2.066



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Abstract

Multiple Sclerosis is a brain disease that forms the number of lesions in white matter of brain as the disease progresses. In this paper texture analysis is done on brain MRI Images of real data of patients to observe the progress of disease by detection. The objective of this paper is to find the progression detection by utilizing the segmentation and feature extraction techniques. The image is segmented using the AM-FM segmentation, the filtering is done by using Saliency map method and these filtered segmented features are clustered using Fuzzy C means clustering method. The paper also proposes an adaptive iterative threshold based algorithm for detection of lesion from the clustered image. The detected features are extracted using feature extraction techniques such as morphological, local binary pattern, mean and standard deviation methods. These extracted features are classified using K-NN classifier. The experimental results obtained are efficient and provides an accuracy of 97% which helps in accurately predicting a disease. Along with detection and classification the patch based algorithm is used for reconstructing the damaged images.

Keywords

Magnetic Resonance Imaging (MRI), Amplitude-modulation, Frequency-modulation (AM-FM), Multiple Sclerosis (MS) Silencing Map Detection, Fuzzy C-means Clustering (FCC), Texture analysis

Received: 30 April 2016; **Revised:** 30 June 2016; **Accepted:** 25 August 2016;

Published: 31 August 2016;

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Introduction

The central nervous system consists of two components gray matter and white matter. The brain disease multiple sclerosis appears in brain white matter and spinal cord. It appears due to damage of myelin sheath of nerve fibers. This further develops no. of multifocal lesions in the central nervous system which relates with the disease progression. Due to formation of lesions, volume of white matter shrinkages [1]. Multiple sclerosis (MS) normally appears in the age between 20-50 years and it affects more to women than men. The initial diagnosis based on clinical signs and symptoms is done by specialized neurologist [2]. McDonald criteria are followed by neurologist to see the disease progression with EDSS score. Several preclinical tests are helpful in disease verification. Magnetic Resonance Imaging (MRI) is one of the techniques to see the multifocal lesions in central nervous system. This relates to MS with the use of T2 weighted images. But still 5% patients who have been confirmed to have MS based on other criteria cannot observe in MRI. To cater this drawback, a texture analysis method is applied on multiple sclerosis in brain MRI images. Texture features can be significantly used to differentiate between normal and abnormal tissues. To avoid the intensity variation between successive scans of MRI, intensity normalization is applied on brain MRI [3]. The multiple image segmentation and feature extraction technique has been used to find the region of interest and lesion features in order to detect the disease in its initial stages. It will also be useful to see the progression of disease. The detection of disease in earlier stages helps to predict the type of disease with the patient might be suffering. The dataset of normal brain MRI images and real patient brain MRI images carrying MS is collected from reputed hospital with reference from Radiologist and Neurologist. The data of 20 patient images in the age between 20 to 45 of both men and women have been taken. Out of the total Dataset some cases are identified as of progressive weeks and some are of initial stages.

Review of related work

Yunyan Zhang (2012) describe that texture analysis is an image post processing approach that extracts quantitative information from a digital image based on mathematical analysis. At two dimensional MR images is a digitized picture of elements (pixels) characterized by spatial location and gray level intensities. MRI texture analysis evaluates the organizational pattern of image pixels. Texture features are in fact mathematical parameters that highlights the distribution of gray level intensities to reflect the structural regularity of image tissues [4]

Jing Zhang, Lei Wang, Longzheng Tong (2007) focuses on application of texture analysis on MR images which extract the classical texture analysis features to differentiate between normal appearing white matter (NAWM), normal white matter (NWM) and MS. The study demonstrates an accurate high texture classification is high between MS lesion and NAWM or NWM also the classification is low between NAWM and NWM due to differences in selected features [5]. The classification rate mentioned is 90%.

Victor Murray, Eduardo S. Barriga, Peter Soliz, Marios S. Pattichis focuses on the use of AM-FM method in series of medical Imaging problems ranging from ultrasound to retinal image analysis like carotid artery, ultrasound pneumoconiosis, diabetic retinopathy and age related macular degeneration [6]

Victor Murray, Paul Rodríguez, and Marios S. Pattichis proposes (2010) an development of new multiscale AM-FM demodulation method for image processing. The approach based on the three

basic ideas (i) AM-FM demodulation using a new multiscale filterbank (ii) new accurate method for instantaneous frequency (IF) estimation (iii) Multiscale least squares AM-FM reconstructions [7].

Mohsen Ghael, Athony Traboulsee, Rabab K. Ward (2006) demonstrates the method based on optimal filter design for maximal feature selection and separation. The designed optimal filter separates the texture features and energies of two main classes within the prescribed ROIs i.e. MS lesions and normal white matter. The MS lesions have been transformed to brighter areas with increased intensity while the background (healthy white matter tissue) has been transformed to darker areas [8]

C.P. Loizou, V. Murray, M.S. Pattichis, I Seimenis, M. Pantziaris, C.S. Pattichis (2011) introduces the use of multiscale AM-FM texture analysis of MS using magnetic resonance (MR) images from brain. It proves the association between lesion texture and disease progression. The finding suggested that AM.FM characteristics succeed in differentiating between 1) NWM and lesions 2) NAWM and lesions 3) NWM and NAWM. The AM-FM feature provide complementary information to classical texture analysis features like the gray scale, median contrast and coarseness. The further future work is suggested for finding additional AMFM texture features that will provide information to differentiate between NAWM & MS lesions. The extracted AMFM features could possibly offer additional information of not yet developed lesions. The accuracy of classification mentioned here is 86% [2]

T. Liu, J. Sun, N. Zheng, X. Tang, and H. Y. Shum (2007) Paper proposes a set of novel features including multiscale contrast center surround histogram and color spatial distribution to describe a salient objects locally, regionally and globally [9].

V. Shiv Naga Prasad, Jastin Domke specifies a system for the visualization of a difficult multidimensional space. The space of a Gabor filter bank response to an image. It also gives an idea to view the four dimensional space through 2 dimensional projection [10].

C.P. Loizou, I Seimenis, M. Pantziaris C.S. Pattichis (2009) discusses the problem that arises occur in texture analysis and quantitative analysis of MRI. In this an extracted regions are not comparable between consecutive or repeated scans. Also it is not comparable within the same scan between different anatomic regions. The reason is that there are intrascan and interscan image intensity variations due to the MRI instrumentation. The six different image intensity normalization methods is further proposed. One of which should be applied to MR images prior to further image analysis [3].

Case study of patients

Case / Patient's Name : abc

REF.BY : MEDICINE V

MRI BRAIN

Protocol of Sequences: Axial T1, T2, FLAIR, DWI B1000, sag T2, COR T2 FLAIR

Clinical details: c/o weakness in left upper and lower limb since 15 days.

FINDINGS AND IMPRESSION:

- Two vertical altered signal intensity lesions are noted in the body of the corpus collusum appearing hyperintense of T2WI and FLAIR and hypointense on T1WI, involving whole length of the corpus collusum. Associated thinning of the corpus collusum is noted.
- Few altered signal intensity areas are noted in bilateral centrum semiovale appearing hyperintense on T2WI and FLAIR and hypointense on T1WI. These lesions appears to be perpendicular to the

corpus collusum. These lesions most likely suggest white matter plaques. Needs further interval follow up MRI study to rule out Multiple sclerosis.

- Rest of the cerebral hemispheres reveal normal morphology and signal characteristics. The hippocampal regions appear normal in signal characteristics and are symmetrical.
- The basal ganglia internal capsules and thalami reveal normal morphology and signal intensity.
- The ventricular system, cisterns and sulcal spaces are normal.
- Pituitary gland appears normal. The parasellar regions appear normal.
- The posterior fossa structures viz cerebellum, brain stem and basal cisterns reveal normal morphology and signal intensity.
- Incidental finding of mega cisterna magna is noted.
- The intracranial vascular flow voids and venous sinuses are normal.
- The visualized paranasal sinuses are normal.

Name:-	ABC 2	AGE/SEX	32YRS/M
Reg no:-	12563	DATE	02/11/2015
Referred by:-	aaa	MRI NO	151102-03
Performed by:-	asd	WD/OPD	OPD
Protocol:-	MRI BRAIN PLAIN AND CONTRAST STUDY		

Case II CLINICAL HISTORY:- C/O headache since 8 days and seizure 2 episodes.

TECHNIQUE: MRI brain has been performed using T1, T2 and FLAIR, diffusion weighted axial, T2 weighted coronal, T1 weighted sagittal sequences.

OBSERVATION:-

- There are multiple altered signal intensity of varying size noted in subcortical white matter predominantly in right periventricular region and juxta cortical, largest measuring 1x1cm appears
 - Hypointense on T1WI, Hyperintense on T2 and FLAIR.
 - Showing diffusion restriction and no areas of blooming on FFE.
 - Not associated with perilesional oedema.
 - Few of lesions showing enhancement on contrast.
- Rest of Brain parenchyma shows normal gray-white matter differentiation.
- In the Infratentorium, the Brainstem, the Cerebellum and the Fourth ventricle appear normal.
- The Third & lateral ventricles appear normal. The Midline structures are normally oriented.
- Sella and parasellar region appear normal. The Basal Cisterns are clear.
- Collection noted in bilateral mastoid air cells.
- Flow voids in the intracranial vessels are well maintained.
- Visualized portions of orbits and the paranasal sinuses show normal morphology.

IMPRESSION: MRI Brain Plain and contrast study reveals multiple altered signal intensity of varying size in subcortical white matter predominantly in right periventricular region and juxta cortical s/o demyelinating disease possibly Multiple Sclerosis.

Segmentation Methods

AM-FM Method

AM-FM method fragments the image into spatially changeable sinusoidal waves and their spatially-changeable amplitudes [7].

AM-FM representation is given as follows.

$$I(x, y) = \sum_{k=1}^k a_k(x, y) \cos(\phi_k(x, y)), \quad w_k(x, y) = \nabla \phi_k(x, y) \quad (1)$$

AM-FM is a 2D Signal (image) processing technique applied to different medical imaging problems. Over multiple scales they provide a physical meaningful texture features at pixel level resolution. The AM-FM segmentation of brain MRI images is implemented in Matlab GUI Figure 1(a) and (b) shows varying amplitude and angle which in turn varies the frequency of the image. Where Fig 1 (a) is input image and Fig 1(b) is an output image.



Figure 1. (a) Input MRI Image



Figure 2. (b) AM-FM Segmented image

Saliency Map Detection

The saliency detection model is proposed by Itti.al. The three features i.e. intensity, color and orientation of images are used to find the saliency map. The salient region i.e. tracking of identified object from the image, a hyper complex form and Gaussian filter is used. The saliency map image is shown in figure 2 [9]



Figure 3. (a) Cognitive Normal Brain



Figure 4. (b) Saliency Map image of Brain

The saliency map is an explicit representation of image objects. In this section, we study simple threshold segmentation to detect image-objects in a saliency. Given $P(x)$ of an image, the object map $T(x)$ is obtained [11]

$$T(x) = \begin{cases} 1 & \text{if } P(x) > \text{threshold}, \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

Empirically, we set $\text{threshold} = M(P(x)) \times 3$, where $M(P(x))$ is the mean intensity of the saliency map. The selection of threshold is a trade-off problem between false alarm and neglect of objects [10]. While

the object map $T(x)$ is generated, image-objects can be easily obtained from their respective positions in the input image. Numerous targets are extracted consecutively.

Fuzzy C-Means Clustering

Author Bezdek in 1981 introduced Fuzzy C-Means clustering method; FCM is widely applied in medical image analysis and diagnosis. It is a data clustering technique based on Ruspini Fuzzy clustering theory in 1980's. Pixels are bunch depending on the value of intensity and spatial features. Further clusters are combined to get the result of final segmentation [12]. A set of data is grouped into k clusters with each data point in the dataset related to each cluster. It will have a high degree of connection to the cluster. Another data point that lies far away from the center of a cluster will have a low degree of connection.

O is fixed where o is ($2 \leq o \leq k$) and then select a value for parameter ' r ' and there after initialize the partition matrix $P(0)$. Each step in this algorithm will be labeled as ' s ' where $s = 0, 1, 2 \dots 1$)

Initially o centric vector V_{xy} is calculated for each step.

$$V_{xy} = \frac{\sum_{n=1}^k (P_{in})^r x_{ky}}{\sum_{n=1}^k (P_{xy})^r} \quad (3)$$

Now the distance matrix which is calculated as

$$D_{[c,k]} D_{xy} = \left[\sum_{y=1}^r (w_{ny} - v_{xy})^2 \right]^{1/2} \quad (4)$$

Finally the partition matrix for the s^{th} step, $P^{(O)}$ is updated as,

$$p_{xy}^{s-1} = \left[\frac{1}{\sum_{y=1}^c (d_{xn}^s / d_{yn}^s)^{2/r-1}} \right] \quad (5)$$

$\|P(k+1) - P(k)\| < \delta$ then it should be stopped otherwise back to step 2 by updating the cluster centers iteratively and the membership grades for data point [13]. FCM iteratively moves the cluster centers to the right location within a dataset [14].

Adaptive Iterative Threshold Based Algorithm

The Adaptive iterative threshold based algorithm is designed which provides a fined grained segmentation. It gives a region of bright intensity. A threshold is set by finding the mean of all non zeros values of defined matrix image. The value below threshold will be zero which shows the darker components. A brighter component shows the non zero values in each iteration. The iteration value must be kept optimum to get the optimized output.

Iterative threshold based algorithm is designed a follows. For example consider a image having pixel values as follows.

$$\begin{array}{ccc} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{array}$$

The mean value of matrix is

$$\frac{\sum_{i=1}^n S_i}{n} \quad (6)$$

Where S_i is sum of all pixel values of matrix & n is total pixel values of matrix.

For above matrix, threshold value is $45/9=5$, The values below threshold are set to zero.

At iteration 1 matrix is

$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 5 & 6 \\ 7 & 8 & 9 \end{bmatrix}$$

For this threshold value is $35/7=5$. At iteration 2 matrix is

$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 7 & 8 & 9 \end{bmatrix}$$

Repeat the above steps for more iteration. In this paper more appropriate results are obtained at iteration number 2.

Feature Extraction Techniques

Morphological features

The features like area, eccentricity, major axis length, minor axis length and orientation are extracted from black and white segmented images.

Local binary pattern

It is a powerful method for texture classification. It summarizes the local structure in an image by comparing each pixel with its neighborhood [15]. There are total 2^8 i.e. 0 to 255 possible combinations of features extracted from gray level segmented images.

Hierarchical centroid and Gabor filter

For Hierarchical centroid Agglomerative method is used. These are post feature extraction techniques. The features are extracted in terms of mean and standard deviation of Gabor filter [10]. A four scale filter bank is used.

Classifier

A machine learning algorithm called K-NN classifier which is a linear classifier is used to classify the healthy and diseased images. It also categorizes the images into different classes to see the progression of disease.

Reconstruction

The Quality of the MRI images depends on the MRI acquisition parameter. If the images are not proper or damaged at some part, a reconstruction is applied on that part. A patch based reconstruction is used to replace the noisy patch by best matching patch of the image. This is done to reconstruct the area of damage as shown in figure 3. The medium mean square error and peak signal to noise ratio values are calculated on a patch by patch basis to remove additive or multiplicative noise after reconstruction [16]. is as shown in figure 4.

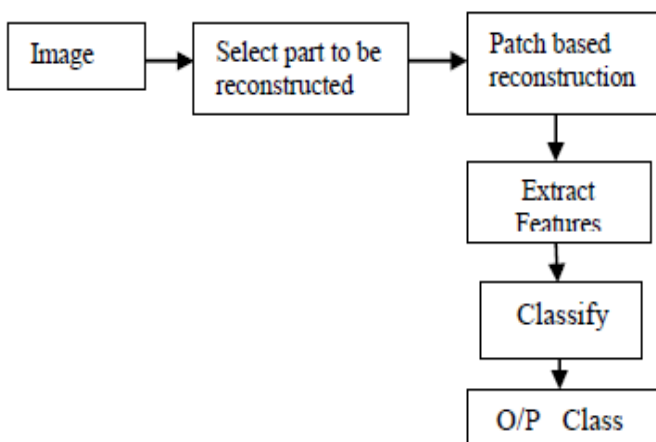


Figure 5. Block diagram of MRI image reconstruction

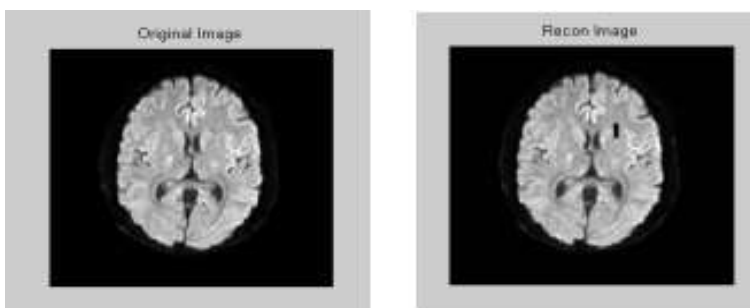


Figure 6. (a) Original image (b) Reconstructed image (Arrow showing the reconstructed patch of image)

After reconstruction of different patient images, the value of medium mean square (MMSE) and peak signal to noise ratio (PSNR) for different MRI images are obtained as follows. MMSE varies from 0.00002675 to 0.014460. PSNR varies from 36.7963db to 95.7565db. Both PSNR and MMSE depend on quality of image.

Proposed Work

The proposed methodology consists of two phases:-

1. Training Phase and
2. Evaluation Phase

The complete schematic representation of the proposed work is as shown below.

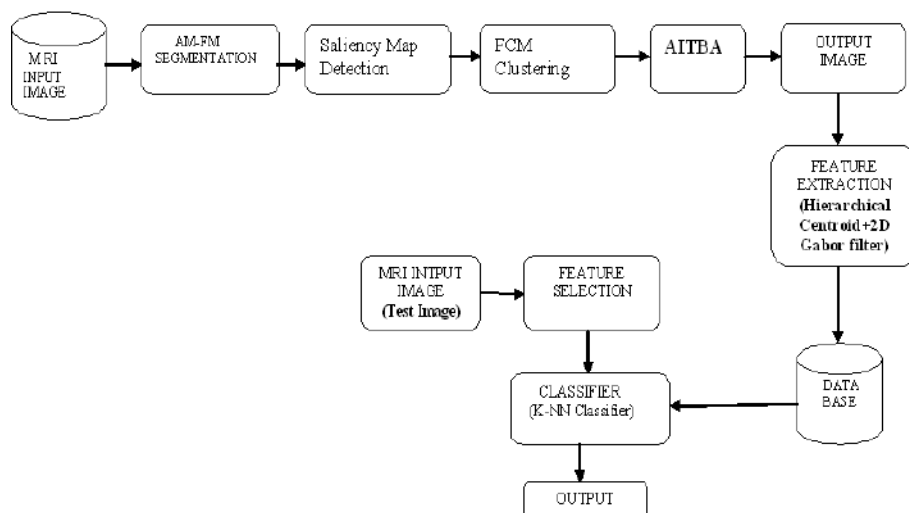


Figure 7. Representation of work flow diagram.

Training Phase

The database is used to train the complete system. The MRI image of the brain is taken as the input. AM-FM Segmentation is used for the image processing Saliency map detection technique is used to find out the region of interest and important area of the image. The output image from the saliency map detection segmentation is the image which has only salience image. FCM clustering algorithm is applied on the salience image to calculate the infected regions in the MRI images. All the infected regions are counted. Adaptive Iterative threshold based algorithm is developed to get the brighter part of image. The output image from the AM-FM segmentation is used for getting the features from the image. Features extraction is used in terms of 1) local binary pattern 2) Hierarchical centroid 3) fs and fm of segmented image 4) morphological features.

Evaluation Phase

The features are stored in the database with the name of the disease for the evaluation phase. The progress pattern of the patient is calculated in the evaluation phase and compared with the pattern stored in trained database. This will help to predict the future state of the patient with the matching pattern patient history.

Output representation of proposed work



Figure 8. (a) Brain MRI MS image



Figure 9. (b) Segmented image

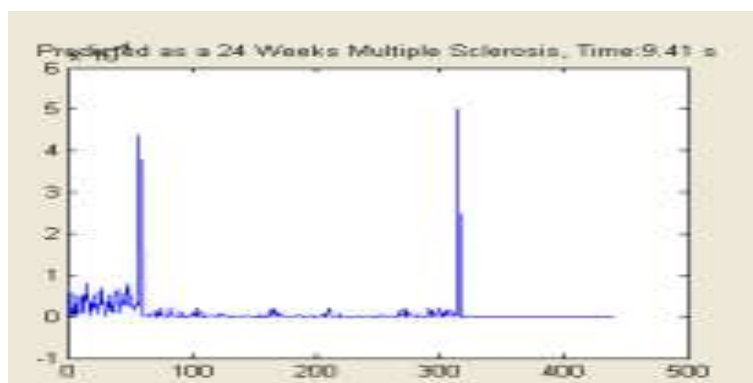


Figure 10. (c) Extended feature amplitude



Figure 11. (a) Brain MRI MS image



Figure 12. (b) Segmented image

Result & Discussion

The images of real patient carrying MS for progressive weeks (up to 96 weeks untreated) are collected from radio diagnosis centre of various reputed hospitals. These images are used to train the database of which some images are reserved for evaluation purpose. Iteration value must be kept optimum to get the optimized output. The percentage of correctly evaluated images is shown in table 1. Maximum accuracy is obtained at iteration 2 as shown in figure plotted between number of iterations and % accuracy. Moreover the accuracy is best for one week patient which will support for early diagnosis of the disease. Figure 6 & 7 shows the output result which guides to locate the lesion correctly by describing it nearest features. The snapshot of complete analysis of the input brain MRI image (Figure 9) is also shown which highlights an evaluation of progressive detection of disease. In this Figure Axes 1 represents brain MRI image carrying MS, axes 2 represents the segmented image and axes 3 represents extended features amplitude. By utilizing segmentation and feature extraction techniques the accuracy of detection of disease obtained is 97%.

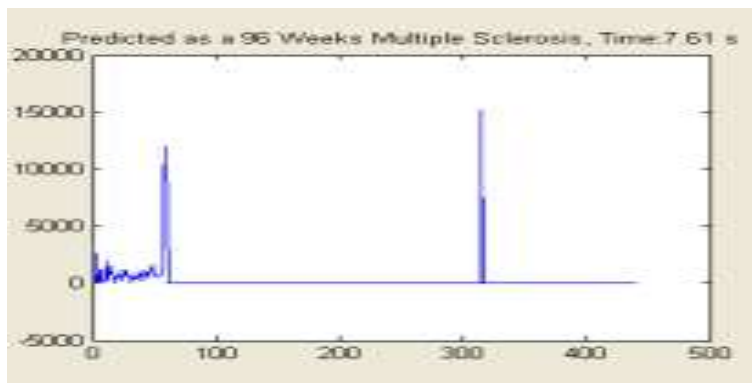


Figure 13. (c) Extended feature amplitude

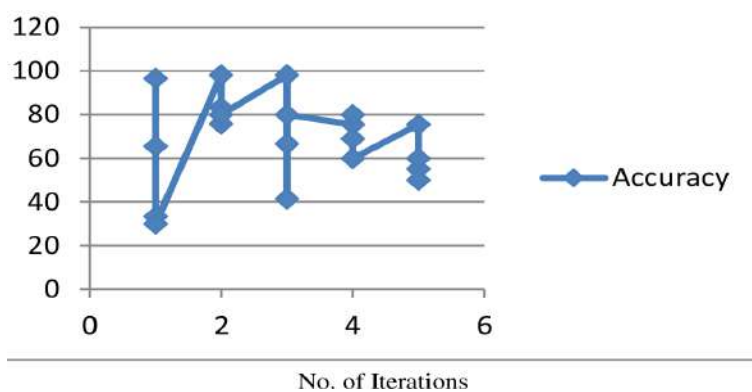


Figure 14. Graphical representation of % accuracy.

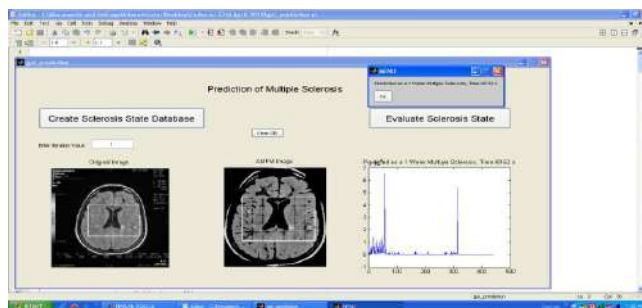


Figure 15. Shows the snapshot of the simulation results for different iteration values (Arrow shows the iteration value)

Table 1. Accuracy of disease progression for brain MRI Images

No. of Weeks	No. of images trained	No. of Iterations	Images used for evaluation	Correct image evaluation	% Accuracy
1	275	1	53	51	96.66
24	53	1	29	19	65.51
96	10	1	06	2	33.33
144	20	1	10	3	30
1	275	2	53	52	97.77
24	53	2	29	22	79.31
96	10	2	06	05	83.33
144	20	2	10	08	80
1	275	3	53	52	98.11
24	53	3	29	12	41.37
96	10	3	06	04	66.66
144	20	3	10	08	80
1	275	4	53	40	75.47
24	53	4	29	20	68.96
96	10	4	06	04	80
144	20	4	10	06	60
1	275	5	53	40	75.47
24	53	5	29	16	55.17
96	10	5	06	03	50
144	20	5	10	06	60

Conclusion

A very closed analysis over the evaluation of various images obtained of different patients for different weeks have been carried out. It has been concluded that as the no. of iteration increases beyond 2, the accuracy go on reducing for progressive weeks of disease detection of the patient. This Identify the optimum value of iteration is 2. Moreover, the accuracy is best for the patient during diagnosis in the very first week which helps to early diagnose the disease that let the patient to know about the prediction of his/her health condition. This shall help to find out the accurate detection of severity of the disease already progressed in the patient

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